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R. Andrew Allison

James E. Foster

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Harvard Center for Population and Development Studies
9 Bow Street
Cambridge, MA 02138

phone: 617 495-2021
fax: 617 495-5418
e-mail: cpds@hsph.harvard.edu

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R. Andrew Allison

James E. Foster

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R. Andrew Allison
Professor James Foster
Department of Economics
Vanderbilt University
Box 1819 B
Nashville, TN 37235

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ABSTRACT

Many questions in health policy require an understanding of the distribution of health status across a given population and how it changes as a result of policy interventions. Since objective data on individual health status are often unavailable or incomplete, especially for populations with very low mortality, increasing use has been made of Self-Reported Health Status (SRHS) data, which record people's own perceptions of their health status. SRHS has been shown to be a strong predictor of objective health outcomes and indications, including mortality. Nevertheless, the qualitative or categorical nature of SRHS data prevents the straightforward use of traditional tools of distributional analysis, such as the Lorenz curve, in evaluating inequality. This paper presents a methodology for evaluating inequality when the data are qualitative rather than quantitative in nature. A partial inequality ordering is defined to indicate when a distribution is more "spread out" than another; a second partial ordering (first order stochastic dominance) is used to indicate when the overall health level rises. Both are applicable to qualitative data, such as SRHS, in that results do not depend on the numeric scaling assigned to the categories. The approach is illustrated using SRHS data from the *National Health Interview Survey* and *NHIS State Data Files* for the 1990-1994 period, focusing on the distribution of SRHS within ages and states.

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1. INTRODUCTION

Many key questions in health policy require an evaluation of the inequality in the distribution of health status across individuals in a population, and how that level of dispersion might be altered through policy reforms. Objective data on individual health status, however, are often unavailable or incomplete or are difficult to interpret, especially for groups with very low mortality.[1] Consequently, several studies have turned to data on Self-Reported Health Status (SRHS) – which provides a respondent's own perceptions of their general health condition -- in constructing an aggregate health profile.[2]

There are a number of potential advantages of using SRHS. First, it allows the individuals themselves to determine the relative importance of the various dimensions of health, rather than assigning arbitrary weights to the components. Second, there is a great deal of evidence that SRHS is a strong predictor of objective measures of health.[3] And third, SRHS is widely collected, and is therefore available in large enough samples as to allow meaningful analysis of a broad range of questions. There are also a number of potential problems with SRHS, including the possibility of inherent biases due to the fact that it is self-reported rather than objectively determined; the relative merits of these arguments have been discussed at some length elsewhere. [4]

A critical limitation of SRHS data in evaluating the distribution of health is its qualitative nature. Respondents assess their health in various ranked categories rather than along a given cardinal scale. The US *National Health Interview Survey* (*NHIS*), for example, has five categories for respondents: poor, fair, good, very good, and excellent. Given this central feature, a key question is how to interpret the distributional information imparted by SRHS data. In particular, to what extent can standard measurement techniques used in income inequality analysis be applied in this context?

In order to make use of the standard techniques, one must first select a scale which assigns a numerical value to each category of health. A natural choice is the "linear" scale, assigning the values "1,2,3,4 and 5" to the respective categories "poor, fair, good, very good, and excellent." One can make a reasonable argument in favor of such an approach – that in the absence of any additional information about the "distance" between categories, one should simply use an equidistant scale.[5] Indeed, precedent for such a scale can be found in the work of Deaton and Paxson (1997, 1998), who examine SRHS inequality over the life-cycle.[6]

The use of a specific scale along with standard methods of evaluation can be a good starting place for analyzing health inequality. However, it is clear that any given scale can be challenged; and an alternative scale may significantly alter the initial conclusions. Put differently, any results obtained using a single numeric scale may not hold up under further scrutiny. How can we be sure that a given conclusion is robust? Is there a technique for evaluating health inequality that is independent of scale?

This paper presents an "ordinal" approach to evaluating health inequality that is robust to changes in the scale. We begin in Section 2 with a critique of "mean-based" inequality measures when the underlying variable is qualitative. In Section 3 we present our median-based approach, which views inequality as a "spread" away from the median. The overall approach is embodied in a simple diagram that (analogous to the Lorenz curve) graphically indicates when inequality rises or falls. Associated with this diagram are several basic measures of spread which are helpful in signaling and explaining changes in health inequality. Sections 4 and 5 present two applications of these tools using U.S. data. The first examines inequality in health over the life-cycle, while the second compares health inequality across states. The final section summarizes our results and suggests promising avenues for future investigation.

Before proceeding to the analysis, we would like to emphasize that the aim of this paper is to provide a method of evaluating *overall* inequality in health, without focusing on any particular cause or justification. In this respect, we are following the traditional objective of income inequality measurement (see, for example, Atkinson, 1986, or Sen, 1997), which has periodically been advocated for assessing health inequality (see, for example, Tobin, 1970, Muurinen and Le Grand, 1985, or Culyer and Wagstaff, 1993). In essence, it is an attempt to describe "what is", which logically precedes analyzing the causes of inequality or judging the extent to which observed differences are inequitable.[7]

At the same time, we recognize that there are many useful studies whose main purpose is to identify the possible causes of inequality. In labor economics, "earnings equations" provide estimates of the importance of education, race, gender and other variables to one's level of earned income, and thereby help to explain observed levels of inequality in this important component of income. For health, an analogous exercise gives an assessment of the level of "socioeconomic inequalities in health" by evaluating how an individual's or a group's level of health depends on its social or economic status.[8] These types of studies provide important clues to certain facets of health inequality, which become more informative when placed in the broader context of overall health inequality.

2. PROBLEMS WITH THE MEAN

A given population's SRHS distribution will be represented as a vector $x = (x_1, x_2, ..., x_n)$, where n is the (fixed) number of categories and x_i is the number of observations in category i. A scale is a positive vector $c = [c_1, c_2, ..., c_n]$ that assigns category i the numeric value c_i, with the property that higher health categories have higher values, i.e., $c_i > c_j$ for all $i > j$. The mean of distribution x given the scale c is defined by

(1) $$\mu(x;c) = \frac{x_1c_1 + x_2c_2 + \ldots + x_nc_n}{x_1 + x_2 + \ldots + x_n}$$

Traditional measures of inequality such as the variance, the Gini coefficient, Atkinson's measures, the Theil measures, and the other generalized entropy measures are all "mean-based" in that they view inequality as deviation from the mean or are normalized using the mean. In other words, all standard measures have formulas that are substantially dependent on the mean. This has important consequences for their applicability in the present context.

2.1 The non-robustness of the mean as an indicator of societal health

The mean is often used as an indicator of the "aggregate" level of health in a population. Relative inequality measures usually divide observations by the mean to obtain a "normalized" distribution that serves as the measure's primary data. Normalizing by the mean facilitates comparison of distributions with different levels of societal health, aligning the distributions so that deviations from the mean are comparable. In the present context, though, the mean is highly sensitive to re-scalings, and the ranking of two distributions by the mean may not be independent of scale. Consequently, normalizing self-reported health distributions by the mean can be problematic, which in turn casts doubt on the use of standard relative inequality measures.

To illustrate the sensitivity of the mean-ordering to scale, consider distribution x=(2,2,2,2,2) and distribution y=(3,2,1,1,3). Using the "linear" scale c=[1,2,3,4,5], the mean of x is 3.0 and the mean of y is 2.9, so that $\mu(x,c) = 3.0 > 2.9 = \mu(y,c)$. However, if we re-scale the data using c′=[1,2,3,4,10], changing only the value assigned to excellent health, then the mean of x is less than the mean of y, where $\mu(x,c') = 4.0 < 4.4 = \mu(y,c')$. Clearly, the relative ordering of x and y by the mean may depend on the scale. Can such re-orderings occur in a practical setting? Consider a comparison of mean health by age for men and women using U.S. survey data from 1994.[9] The upper panel of Figure 1 reports the mean health values for men and women for nine ages using the linear scale c. The picture painted by this diagram suggests that males enjoy a higher mean health level at each of the chosen ages. In the lower panel of Figure 1, a second, highly concave scale is used to emphasize differences between lesser categories of health, resulting in a reversal of the rankings of mean health across genders for seven of the nine age levels.[10] The answer to the question of which gender is in better health can depend on the numeric scale.

This does not, however, imply that all such comparisons are subject to reversals. In certain cases, a higher mean at one scaling may entail a higher mean for all scalings. Suppose that the fraction of the

overall population in the worst category of health is lower (or no higher) for distribution x than distribution y. Moreover, suppose that this is true for the fraction in the lowest two categories, the lowest three categories, and so forth. Then in an obvious sense, aggregate health is greater in x than y since, for each category, x has a higher percentage of the population than y in that category or above, and a lower percentage in that category and below. It is not difficult to show that x has a higher mean than y for every possible scale c. This unambiguous ranking of distributions is well-known in other contexts as first-order dominance, and can be defined as follows:[11] x *first order dominates* y, written x FD y, if

(2a) $$\frac{\sum_{i=1}^{k} x_i}{\sum_{i=1}^{n} x_i} \leq \frac{\sum_{i=1}^{k} y_i}{\sum_{i=1}^{n} y_i}$$

for every category k, or, more simply,

(2b) $$X_k \leq Y_k$$

for all k=1,...,n, where $X_k = \sum_{i=1}^{k} x_i / \sum_{i=1}^{n} x_i$ is the cumulative share of the population in the bottom k categories of x, and Y_k is the analogous quantity for y. It is clear from the definition that this ranking of distributions is independent of scale, since it does not mention scale at all. Note that if one were to select a numeric scale, then this definition would be equivalent to the standard definition of first order dominance as a rightward (or downward) shift in the cumulative distribution function, where X_k and Y_k are the respective cumulative probabilities associated with the value c_k. The inequalities $X_k \leq Y_k$ ensure that x has greater weight on higher values, and hence a higher mean for any scale. We have the following result, whose formal verification is given in the Appendix.

Theorem 1 One distribution, x, first order dominates another, y, if and only if the mean of x is as large as the mean of y for every scale c.

Theorem 1 is a reinterpretation of a standard result from stochastic dominance analysis which relates first order dominance to higher expected utility for arbitrary increasing utility functions. Each re-scaling corresponds to a different increasing function, so that the mean for a specific scaling corresponds directly to expected utility. As an example of the theorem, consider distributions x=(1,4,3,6,3) and y=(2,4,4,4,3), which both contain data for a population of 17 respondents. The share of the population in the lowest category is clearly greater for y than x (Y_1=2/17 > X_1=1/17); the sum of the bottom two categories is greater

for y than x (Y_2=6/17 > X_2=5/17); and so on through the fifth category, where the sums are equal. Consequently, x FD y, and so by Theorem 1 we know that x has higher (or no lower) mean health than y for all scales.[12] The above discussion has emphasized the potential importance of reversals in rankings of mean health due to changes in the scale. It should be noted, though, that even in the presence of first order dominance, a re-scaling can alter the relative sizes of the means and thereby affect the inequality values due to normalization by the mean. Moreover, as we shall now see, there are conceptual problems of a different sort when the measure uses the mean as a standard for evaluating deviations.

2.2 *The non-robustness of the mean as a reference point*

When the variable is cardinal, arbitrary transformations are not admissible and the mean is a stable reference point of the distribution. But when the variable is purely ordinal, so that any re-scaling is possible, the mean's location relative to the distribution (or any subset of observations) can vary widely with changes in the scale. For example, the mean of the distribution x=(1,3,3,6,4) given the scale c=[1,2,3,4,5] is $\mu(x;c)$=3.53, which is located between the seventh lowest observation and the eighth. Yet when the scale c′=[1,2,3,4,8] is used, the mean becomes $\mu(x;c')$=4.24, which falls between the 13th and 14th observation out of 17. Recalling the categorical nature of the original data, it is difficult to accept the notion of a central reference value that jumps across categories and observations with such ease.[13]

Now even if the sensitivity of the mean to re-scaling is not considered to be inherently objectionable, it may still pose serious problems for measuring inequality using standard tools, given their dependence on the mean as a reference point from which deviations are gauged. For example, applying the variance σ^2 to distributions x=(1,3,3,6,4) and y=(2,4,4,4,3) yields $\sigma^2(x;c) < \sigma^2(y;c)$ under the linear scale c. With the alternative scale c′=[1,2,3,4,8] the ranking becomes $\sigma^2(x;c') > \sigma^2(y;c')$. This reversal is at least partly due to the repositioning of the means of the distributions when the scale changes. For if the variance of each is evaluated at the *old* scale but using the *new* mean values, this still causes a reversal of the original ranking.[14] In other words, the non-robustness of the mean as a reference point can itself be responsible for the non-robustness in inequality comparisons as the scale is varied.

2.3 *Alternative reference points*

If the mean is unsuitable as a reference point in this context, then what alternative standard should be used? The above discussion has shown that the basis of the problem lies in the mean's undue sensitivity to the chosen scale. We should restrict consideration to concepts that are in some sense robust to changes

in the scale. Moreover, given the ultimate use of the reference value as the standard against which deviations are to be evaluated, it should be "central" in some "space."

One possibility would be to select the health status associated with the middle category ("3" in the linear scaling) as the fixed standard of comparison. To be sure, a change in scale would have no effect on the relative position of the reference point in the distribution. And in an obvious sense, it is at the center of the set of possible health statuses. However, it is equally clear that this approach goes too far in the direction of insensitivity, since it pays absolutely no attention to the specific distribution under consideration. For example, if most of the observations in a given distribution were initially at the lowest health status, while the rest were at the second lowest, a change in the distribution that lowered all observations to the lowest status would *increase* inequality when measured as a function of the deviations from the reference point. And, yet, since all observations are now at the same level, the new distribution is clearly *more* equal. Using a fixed health status as a reference level for inequality analysis can hardly be justified.

On the other hand, "people space" has a natural center at the 50th percentile, which would suggest the use of the median health status m(x;c) as a reference level. It is clearly responsive to significant changes in the distribution – the median is always located at the position where half the population has a health status below (or equal to) it and half is above (or equal to) it. In particular, unlike a standard fixed in "category space," the median will always be the commonly held health status when the distribution is completely equal. At the same time, the median is not too responsive to changes in scale: if i is the median category in x under c, so that c_i=m(x;c), then i is the median category under any other scale c′, i.e., c'_i=m(x;c′). Unlike the mean, the relative position of the median does not change as the scale changes. It is for these reasons that we adopt the median as our standard for evaluating inequality.

3. A MEDIAN-BASED APPROACH

Our approach to measuring health inequality is perhaps best introduced with the help of a simple example. Let x=(4,5,7,5,4) and y=(3,4,11,4,3) be two distributions under consideration, and take c=[1,2,3,4,5] to be the scale. Notice that 3=m(x;c)=m(y;c) is the median of both distributions. Furthermore, two persons with median health in y have lower health statuses (1 and 2) in x, while two other persons in the median category in y have higher statuses (4 and 5) in x. The remaining persons have unchanged status. Consequently, distribution x is in an intuitive sense more "spread out" than y. This relationship can be visualized with the help of a graph. Figure 1 depicts the cumulative distribution functions (CDFs) of x and y given c. Notice that the CDF for x takes on the values (.16, .36, .64, .84, 1.00) at the scale levels 1,2,3,4,5, respectively, while the cumulative values for y are (.12, .28, .72, .88, 1.00). The dashed line halfway up the

vertical axis cuts both CDFs at the common median level of 3. For each status below the median, the CDF of x is above the CDF of y; while for categories above the median the opposite is true. Distribution x has greater inequality than y in that more of its mass is concentrated in the extremes, unambiguously further away from the median.

This intuitive notion of inequality as "spread away from the median" can be more rigorously defined as follows: we say that x has *greater spread* than y, written x S y, if (i) x and y have the same median category m, (ii) for all categories $k < m$, we have $X_k \geq Y_k$, and (iii) for all categories $k \geq m$ we have $X_k \leq Y_k$, where, as before, X_k and Y_k are the respective cumulative population shares of the bottom k categories. In other words, y first order dominates x below the median while x first order dominates y for the median category and above -- a relationship that might be termed a "median preserving spread." As can be verified from Figure 2, this is precisely the relationship between x and y in our example. Of course, not all pairs of distributions are related to one another by a median preserving spread. Consequently, the ranking S is a *partial ordering* of distributions that is *reflexive* (x S x for any x) and *transitive* (x S y and y S z implies that x S z, for any x, y, z), but not *complete* (since for some x and y we have neither x S y nor y S x).[15] In this way it is similar to the well-known Lorenz ranking of income distributions.

The partial ordering S can be represented by a graphical tool we call the "S-curve," which is derived from the CDF as follows. [16] First, the portion of the CDF to the right of the median health status is flipped over to the left, as shown in Figure 3. The resulting curve is then rotated 90 degrees to obtain the S-curve depicted in Figure 4. Note that the base of the S-curve represents the range of the population having the median level of health. Just outside of this range are the two groups that are one category away from the median; and beyond this are the groups that are two categories from the median. Now suppose that one distribution has an S-curve that is "closer in" or "higher" than another. As we move outward from the median person along the S-curves, the one that is higher departs from the median earlier and hits every subsequent category sooner, indicating that a greater share of the population is further away from the median. Thus a higher S-curve indicates greater inequality according to the ranking S. Conversely, if the S-curves cross, then it is immediate that the two distributions cannot be compared using S. We have the following result whose formal proof can be found in the Appendix.

Theorem 2 Let x and y be two distributions having the same median category. Then x S y if and only if the S-curve of x is no lower than the S-curve of y.

The S-curve represents S in much the same way as the Lorenz curve represents the Lorenz ranking of income distributions.

Several useful indexes of "spread" can be derived from the S-curve analogous to the way that the Gini index is obtained from the Lorenz curve. Let $s(x;c)$ be twice the area below the S-curve of x, while $s_L(x;c)$ is twice the area to the left of 0.50 and $s_H(x;c)$ is twice the area to the right, as depicted in Figure 3. Since c is the linear scale, the height of the S-curve is the number of health categories that the associated observation departs from the median. Consequently, $s_L(x;c)$ is the average number of categories that the lower half of the distribution falls below the median, while $s_H(x;c)$ is the average number that the upper half is above the median. They are measures of the "lower spread" and "upper spread" respectively. Clearly, $s(x;c) = s_H(x;c) + s_L(x;c)$ is the average number of categories that the higher group is above the lower group, a natural if crude indicator of the overall spread of the distribution.[17] By construction, each is consistent with the S ranking in that x S y implies $s_L(x;c) \geq s_L(y;c)$, $s_H(x;c) \geq s_H(y;c)$ and $s(x;c) \geq s(y;c)$. The converse, of course, does not hold, since the area below the curves could be larger even when curves cross.

Up to now, we have focused on the cumulative distribution functions, the S-curves, and indexes associated with the linear scale c=[1,2,3,4,5]. Our original goal was to find a method of evaluating inequality that is independent of scale. So let us select some other scale c′ and examine what happens when it is used in place of c. Clearly, the CDFs are stretched or compressed horizontally according to the new values assigned to categories, but the magnitude of the vertical jumps are unchanged. As mentioned above, the median category is unaffected, as is the size of the population in this category, and consequently the base of the S-curve is the same as before. The rest of the S-curve is shifted in height reflecting the new distances between category values implicit in the new scale. Its height is no longer the number of health categories between a given observation and the median, but rather the number of health status units between the observation's health status and the median health status.

While the height of an S-curve is altered by a change of scale, the relative positions of S-curves are not. If the S-curve of x is higher than the S-curve of y for a given scale, this relationship remains true at all scales. Consequently the inequality ranking S corresponds exactly to the ranking implied by S-curves for any given scale. This robustness to scale ensures that the ranking S is based purely on the original data and not on the particular scale selected – a characteristic that is evident from the definition of S, which makes no reference to scale. In contrast to the scale independence of the ranking S, the index $s(x;c)$ depends crucially on c, the particular scale employed. For any c, let $\mu_L(x;c)$ and $\mu_H(x;c)$ represent the mean health status for the groups respectively below and above the median. Then $s(x;c) = \mu_H(x;c) - \mu_L(x;c)$, and hence s now measures average distance in terms of health status units rather than number of categories. The magnitude of the index surely depends on the particular scale employed. More importantly, the way that it ranks distributions can depend on the scale, since s is a difference of scale-dependent means.

Following the logic of Theorem 1, we might ask: when can a pair of distributions be consistently ranked by the index s over *all* scales? Clearly, if x S y, then the areas under the S-curves must follow this ranking for any given scale, which is sufficient to ensure a consistent ranking by the spread index. As the following result shows, this is necessary as well.

Theorem 3 Let x and y be two distributions having the same median category. Then x S y if and only if $s(x;c) \geq s(y;c)$ for every scale c.

Thus, the partial ordering S is equivalent to an unambiguous ranking by the spread index s at all scales.

In general, the decision of the spread measure s is influenced by the scale, and hence it may not be appropriate as a final arbiter of inequality when a single scale is used. Nevertheless, it does have a useful role as a partial signal of when S holds. If $s(x;c)$ is greater than or equal to $s(y;c)$ for some c, then x S y is possible; but if $s(x;c)$ is less than $s(y;c)$ for some c, then x S y cannot hold.

The partial spread indexes s_L and s_H provide even greater information about the relationship between two distributions, since they separate out changes below the median from those above. Note that $s_L(x;c) = m(x;c) - \mu_L(x;c)$ and $s_H(x;c) = \mu_H(x;c) - m(x;c)$ must both follow the ranking S, when it applies. It turns out that when s_L and s_H consistently rank distributions for all scales, and are in agreement as to which distribution has greater spread, the distributions are likewise ranked by S.

Theorem 4 Let x and y be two distributions having the same median category. Then x S y if and only if $s_L(x;c) \geq s_L(y;c)$ and $s_H(x;c) \geq s_H(y;c)$ for all scales c.

This result emphasizes the potential usefulness of s_L and s_H as signals for determining when S applies. To find S comparisons in practice, it is useful to compute s_L and s_H for the linear scaling and then to check whether s_L and s_H order the distributions in the same direction. If they do, a ranking by S is possible, and the corresponding S-curves can be further evaluated for the presence of the dominance relation S. On the other hand, if s_L and s_H disagree, a ranking by S is impossible.

Note that a disagreement between s_L and s_H suggests that one distribution has less mass than the other below the median and more above it, which is indicative of the first order dominance relation. Indeed, there is a useful relationship between s_L, s_H and FD as provided by the following result:

Theorem 5 Let x and y be two distributions that have the same median category. Then x FD y if and only if $s_L(x;c) \leq s_L(y;c)$ and $s_H(x;c) \geq s_H(y;c)$ for all scales c.

Intuitively, when s_L unambiguously falls and s_H unambiguously rises, this ensures that the left side of the S-curve falls while the right side rises. By the relationship between the S-curve and the CDF, this is equivalent to first order stochastic dominance.

This section has presented a basic approach to evaluating the distribution of self-reported health that respects the qualitative nature of the data. Our key rankings, S and FD, render judgements only in cases where scale does not matter; otherwise they are entirely silent. This raises a natural issue of how "completely" they rank distributions in practice, which, of course, is an empirical question. The next two sections offer preliminary evidence of the applicability of our approach, and in the process offer insight on how the distribution of health varies over the life-cycle, and across states and regions of the United States.

4. HEALTH OVER THE LIFE CYCLE

We examine the distribution of SRHS over the life cycle using data from the 1990-1994 *National Health Interview Survey (NHIS)*. The *NHIS* is a nationally representative sample of the non-institutionalized population. Approximately 44,000 households are surveyed annually, including over 100,000 individuals of all ages. As a rule, adults respond on behalf of children, while a substantial percentage (30% in 1994) of adult responses are also by proxy. Due to the complex, multi-stage sampling design and over-sampling of certain populations, sampling weights have been appended to the survey data by the National Center for Health Statistics to render the sample representative of the U.S. non-institutionalized population. We apply these sampling weights in all of our analysis.

Using a linear scale for SRHS data from the *NHIS* and *PSID*, Deaton and Paxson (1997, 1998) find that health disperses with age.[18] The middle panel of Figure 5 reproduces their basic results for female respondents using NHIS data from 1990 through 1994. Variance appears to rise monotonically until about age 55, after which the pattern is unclear.[19] The upper and lower panels of Figure 5 illustrate the effect of changing scales. The upper panel uses a convex SRHS scale c=[1, 1.1, 1.4, 2.3, 5], where distances between upper categories are greater than distances between lower categories. Variance appears to be nearly constant until about age 40, after which variance falls. In the lower panel, the concave scale c=[1, 3.7, 4.6, 4.9, 5] is used to emphasize differences between lesser health categories, and the variance of SRHS rises nearly monotonically throughout the life-cycle. Age-to-age variance orderings, e.g., age 40 compared to age 70, are clearly dependent upon the numeric scaling of the SRHS data. Reasonable restrictions on the SRHS scale might narrow the results somewhat. For example, limiting SRHS to a linear or concave scaling appears to eliminate the possibility that variance *falls* over a broad range of the life-cycle. However, without such restrictions, one cannot conclude that dispersion in SRHS increases over the life-cycle.

Instead of using the variance with its obvious dependence on scale, we apply the scale independent methodology proposed above to evaluate the distribution of health for various age groups. As a first indication of potential comparisons, we calculate s_L, s_H, and the median for the linear scaling. If the medians are different for two distributions, or if s_L and s_H disagree on their ranking, then the distributions cannot be related by S. In Table 1, results from cross-sectional *NHIS* data from 1994 are reported.[20] As Table 1 shows, when the median is constant, s_H tends to fall over the life-cycle while s_L tends to rise. Hence, different ages cannot be related by S, which implies that dispersion in SRHS does not unambiguously increase (or decrease) over the life-cycle. According to Theorem 5 above, when s_H and s_L move in opposite directions, it can be a signal of a first order relationship between the compared distributions. The clear pattern observed in Table 1 signals the possibility that ages may be related in a first order fashion: younger age groups first order dominate older age groups. Moreover, the mean health level falls with age (apart from the very old and very young) which by Theorem 1 further indicates a first order relationship. The cumulative frequencies depicted in Figure 6 confirm that, with few exceptions, the younger ages first order dominate older ages in health. The likelihood of being in a given health category, or below, is generally smaller at earlier ages. While the trend in the dispersion of SRHS over the life-cycle is ambiguous, there is an unambiguous decline in SRHS over nearly the entire life-cycle.

It is conceivable that part of the first-order relationship between age and health over the life-cycle could be explained by the correlation between health and income, given the covariation between age and income. As an initial test of whether the first order relationship between SRHS and age is still present after controlling for income, we compare the CDFs of neighboring 10-year age groups within seven income bands.[21] For males, we find that the FD ordering by age is substantially robust to this sort of "control" across the middle age groups. Exceptions to the FD ordering by age are concentrated in the youngest and oldest age groups, e.g., males less than the age of 10 did not generally first order dominate males between the ages of 10 and 20, and males between the ages of 10 and 20 do not generally first order dominate males in their 20s. For these younger age groups, exceptions to the age ordering of health are scattered across income categories. Among older males, exceptions to the age ordering of health are generally concentrated in the lower income categories. For females, the FD ordering by age is stronger: the health-age relationship also holds in the lowest age groups for all income bands. As with males, the health-age relationship weakens for older females. Exceptions to the age ordering of health are even more concentrated in the lower income categories for women than for men. Hence, for the *poor* elderly, the answer to the question of whether mean health decreases monotonically with age will depend upon the scaling of the SRHS data.[22]

5. HEALTH ACROSS STATES

In this section we use our measurement techniques to obtain an initial glimpse of the distribution of health across states and regions of the United States. Much has been said about statewide (aggregate) health levels and how they vary.[23] However, relatively little is known about the distribution of health within states. This is perhaps surprising, since an evaluation of the effectiveness of publicly-funded health programs (such as Medicaid) would seem to require analysis of this type.[24] In any event, it seems reasonable to assume that policy makers would be better able to target health interventions if they had a clearer picture of the distribution of health needs. Hence, a principal motivation for evaluating the distribution of health across states is to provide information that might be useful to those who must decide upon the future course of publicly-funded health programs.

We use SRHS data from the 1994 *NHIS State Data Files*[25] to compare the distribution of health across states, checking for both first order and S relationships. Each state's distribution has been standardized to mimic the age and sex composition of the U.S. as a whole.[26] Following the diagnostic strategy employed in our analysis of health over the life-cycle, we first calculate means, medians, the s index, and its components, s_H and s_L, using the linear scaling for SRHS distributions from the 25 largest states.[27] Results from the adjusted sample are reported in Table 2. Notice first that all selected states have "very good" as their median health category. When the linear scaling is used, the index s can be interpreted as the average number of categories separating those in the upper and lower halves of state health distributions. The average categorical spread between the upper and lower halves of the distribution ranges from about 1.5 in Minnesota and Wisconsin to nearly 2.0 in Alabama. In general, southern states have a wider categorical spread in their distributions of health. Southern states also tend to have lower levels of mean health using the linear scale. Ad hoc state-to-state comparisons of s_L and s_H suggest that it is more typical for the two to disagree. This signals the possibility that, where present, dominance relationships are more likely to be characterized by the first order relation than the S relation.

The results of a comprehensive search for first order and S relations among the 25 largest states are presented in Tables 3 and 4. If a cell in Table 3 contains a "1" then the column state has more overall health than the row state. If a cell in Table 4 contains a "1" then the column state has a more equal distribution of health than the row state. The states are grouped by census region to help identify any regional patterns in the distribution of health. In this selection of states, we find that comparisons can be made in 254 of the possible 300 state pairs, with 199 of these being first order relationships and the remaining 55 being S rankings. Based on the results presented in Table 3 it is clear that southern states tend to be first order dominated by northern, mid-western, and western states.[28] Thus, applying Theorem 1, southern states have

the least health on a per-capita basis, independent of any numeric scaling of the SRHS data. These results are generally consistent with regional orderings by mortality rates, and imply that regional health differences in the U.S. are not limited to the lower tail of the distribution, but persist across the population. The inequality comparisons presented in Table 4 do not suggest a clear regional pattern. Nevertheless, where S relationships can be established, it appears that northern and mid-western states tend to have a more equal distribution of health than southern states.

Interestingly, the above results have important implications for comparisons of health *poverty* as well. Note that a first order relationship between two states ensures that the dominant state has the same or a smaller health poverty rate irrespective of the choice of poverty threshold.[29] Similarly, an S ordering between two states ensures that the more equal state has the same or a smaller poverty rate for all poverty thresholds below the median. If we accept that the poverty threshold in this data should fall below "very good" (the universal median), then unambiguous poverty comparisons of this type are evident in 254 of the 300 possible comparisons. A "1" in a particular cell of either Table 3 or 4 implies that the column state has a lower (or the same) level of health poverty than the row state no matter the poverty line. Therefore, the regional patterns observed in the first order and inequality comparisons above are that much more pronounced when the focus is on poverty.

6. CONCLUSION

We have presented a median-based partial ordering that indicates when there is an increase in inequality in a qualitative distribution of health. We have also introduced in this context first order dominance, which yields unambiguous orderings of aggregate or mean health. In addition, we defined two partial indices of dispersion s_L and s_H, and their aggregate s, and have shown how these indices can act as signals for the two orderings and how they can provide an intuitive measure of categorical spread when used in conjunction with the linear scaling. Our empirical applications have shown the prevalence of first-order relationships in the distribution of health across various sub-populations, including age and state of residence. Moreover, we have obtained preliminary results from a partial inequality ranking that suggest the South may have not only less aggregate health than the rest of the country, but that health may also be less equally distributed in the South.

A potential drawback of our approach is that inequality comparisons are limited to situations in which medians coincide. This can prove to be restrictive, particularly when first order effects are in evidence, causing medians to vary across groups, as illustrated by our analysis of health over the life cycle. Nevertheless, a great many of the evaluations do, in fact, involve common median comparisons, and in

particular *all* of the state-wise comparisons presented above have this characteristic. Thus, this requirement need not be widely restrictive. Other limitations can arise from our reliance on rankings that are inherently incomplete. When two distributions can be compared using the unambiguous partial ordering S, the information conveyed is quite powerful. But when the high standards underlying the ranking fail to be achieved, what can be done? Clearly, one approach is to relax the standards somewhat by limiting the class of allowable scales. For example, one could initially rank the distributions using the index s with the linear scale, and then check for robustness of this ranking over all concave scales.[30] This would in principle yield a "more complete," but still partial, ordering of distributions, which would convey a somewhat less general notion of robustness. It would be interesting to explore whether such a criterion could be developed and, if so, how much additional bite it might have.

Taking this limited scale approach to the extreme, we return to the case of a single scale and hence a complete ranking of distributions. Unfortunately, we also regain scale dependence. We should note, though, that the combination of the s index (or s_L or s_H) and the linear scale c has an additional attraction that other combinations may not, namely, the value s(x;c) indicates how many *categories* separate observations below the median from those above the median, on average. The value s(x;c) has a concrete and easy to interpret meaning that is useful in describing a health distribution, and the same is true for $s_L(x;c)$ and $s_H(x;c)$. Moreover, given this inherent significance, one may with some justification explore the possibility of decomposing s(x;c) across population subgroups having the same median. In fact, it is easy to show that for a distribution x broken down into subgroup distributions $x^1,\ldots, x^m$, having the same median, the overall spread s(x;c) is the weighted average of the group-wise spreads, $s(x^1;c),\ldots,s(x^m;c)$, with weights given by the respective subgroup population shares. This decomposition may prove to be of some use in identifying the source of inequality in a population.

Finally, note that while the above discussion has focused on SRHS data, it is easy to see that the same methodology would be applicable to other categorical variables. For example, subjective measures of happiness[31] have properties quite similar to the health variable we employ, suggesting that our techniques can be used to assess their distribution. On the other hand, there appears to be no direct way of applying our methods when the variable is classified into different numbers of categories in the two distributions being compared.[32] It remains to be seen whether our approach can be extended to cases like this.

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APPENDIX

Theorem 1 Let x and y be any two distributions. Then x FD y if and only if $\mu(x;c) \geq \mu(y;c)$ for every scale c.

Proof Let x and y be any two distributions. A simple calculation yields

(A1) $$\mu(x;c) = c_1 + \sum_{j=1}^{n-1}\left(c_{j+1} - c_j\right)\left(1 - X_j\right),$$

and so

(A2) $$\mu(x;c) - \mu(y;c) = \sum_{j=1}^{n-1}\left(c_{j+1} - c_j\right)\left(Y_j - X_j\right).$$

Now suppose that x FD y. Then, by definition, $Y_k - X_k \geq 0$ for all k=1,...,n-1, and hence $\mu(x;c) - \mu(y;c) \geq 0$ for any scale c. Conversely, if x FD y does *not* hold, then there must be some k=1,...,n-1 for which $Y_k - X_k < 0$. Clearly there must exist a scale $c'=[c'_1,...,c'_n]$ for which the inter-category gap $c'_{k+1} - c'_k > 0$ is so large relative to the other inter-category gaps as to render the entire sum $\sum_{j=1}^{n-1}\left(c'_{j+1} - c'_j\right)\left(Y_j - X_j\right)$ negative.

Therefore, $\mu(x;c') - \mu(y;c') < 0$, which ensures that the condition "$\mu(x;c) \geq \mu(y;c)$ for every scale c" fails to hold.

Theorem 2 Let x and y be two distributions having the same median category. Then x S y if and only if the S-curve of x is no lower than the S-curve of y.

Proof Let x and y be any two distributions with the same median category m. Suppose that x S y holds, so that $X_j \geq Y_j$ for all $j < m$ and $X_j \leq Y_j$ for all $j \geq m$. For ease of notation, denote $X_0=Y_0=0$. Select any population share p between 0 and 1 that is not equal to X_j or Y_j for any j=0,1,...,n. Then there must exist j and j' such that $X_{j-1} < p < X_j$ and $Y_{j'-1} < p < Y_{j'}$, and so by definition, the S-curve value at p is $|m-j|$ for x and $|m-j'|$ for y. Now if $j < m$, then since $X_j \geq Y_j$ we must have $j' > j$, which ensures that $|m-j| \geq |m-j'|$. Similarly, if $j > m$, then $X_j \leq Y_j$ we must have $j' < j$, which leads once again to $|m-j| \geq |m-j'|$. The remaining case where $j = m$ must entail $Y_{j'-1} \leq X_{j-1} < X_j \leq Y_j$, and $j' = j$, and so $|m-j| = |m-j'| = 0$. Therefore, at all such p, the S-curve of x is not

below the S-curve of y. This relationship clearly extends to the remaining values of p by definition of the S-curve.

To show the converse, suppose that x and y do not satisfy x S y. Then for some $j < m$ we must have $X_j < Y_j$ or for some $j \geq m$ we must have $X_j > Y_j$. Pick p between X_j and Y_j. If $j < m$, then at p the value of the S-curve of x must be less than $|m-j|$, while the value of the S-curve of y must be at least $|m-j|$, ensuring that the S-curve of y is above the S-curve of x at p. Similarly, if $j \geq m$, then at p the value of the S-curve of y must be greater than $|m-j|$ while the value of the S-curve of x must be no greater than $|m-j|$, once again implying that at p, the S-curve of y is above the S-curve of x. In either case, the S-curve of y is above the S-curve of x at some p, and so the result is verified.

Theorems 3 and 4 Let x and y be any two distributions that have the same median category. Then the following are equivalent:

(i) x S y.

(ii) $s(x;c) \geq s(y;c)$ for every scale c.

(iii) $s_L(x;c) \geq s_L(y;c)$ and $s_H(x;c) \geq s_H(y;c)$ for every scale c.

Proof Suppose that x and y have the same median category m. A simple calculation yields

(A3) $$\mu_L(x;c) = c_1 + \sum_{j=1}^{m-1}\left(c_{j+1} - c_j\right)\left(1 - 2X_j\right) \text{ and}$$

(A4) $$\mu_H(x;c) = c_m + \sum_{j=m}^{n-1}\left(c_{j+1} - c_j\right)\left(1 - 2X_j\right)$$

and so

(A5) $$\mu_L(x;c) - \mu_L(y;c) = 2\sum_{j=1}^{m-1}\left(c_{j+1} - c_j\right)\left(Y_j - X_j\right) \text{ and}$$

(A6) $$\mu_H(x;c) - \mu_H(y;c) = 2\sum_{j=m}^{n-1}\left(c_{j+1} - c_j\right)\left(Y_j - X_j\right).$$

(i)↔(iii): Suppose that x S y. Then, by definition, $X_j - Y_j \geq 0$ for all j=1,...,m-1 and $X_j - Y_j \leq 0$ for all j=m,...,n-1, and hence $\mu_L(x;c) - \mu_L(y;c) \leq 0$ and $\mu_H(x;c) - \mu_H(y;c) \geq 0$ for every scale c. Conversely, if x S y does *not* hold, then there must be some k=1,...,n-1 for which $X_k - Y_k < 0$ and $k < m$, or $X_k - Y_k > 0$ and $k \geq m$. If the first case applies, then

there must exist scale $c'=[c'_1,...,c'_n]$ for which the gap $c'_{k+1} - c'_k$ is so large as to render the sum $2\sum_{j=1}^{m-1}\left(c'_{j+1} - c'_j\right)\left(Y_j - X_j\right)$ positive, in which case $s_L(x;c') < s_L(y;c')$ would be true.

Similarly, if the second case applies, then there exists c' for which $c'_{k+1} - c'_k$ is so large that $2\sum_{j=m}^{n-1}\left(c'_{j+1} - c'_j\right)\left(Y_j - X_j\right)$ becomes negative, in which case $s_H(x;c') < s_H(y;c')$ is true. Either way, condition (iii) fails to hold, and (i) is equivalent to (iii).

(iii)⇒(ii): Suppose that (iii) holds. Since $s(x;c) = s_L(x;c) + s_H(x;c)$ it follows immediately that (ii) holds as well. Conversely, suppose that (iii) does not hold, so that there is a c' such that $s_L(x;c') < s_L(y;c')$ or $s_H(x;c') < s_H(y;c')$ holds. If the first case applies, then it is clear that $s_L(x;c') - s_L(y;c') = s_L(x;c^\epsilon) - s_L(y;c^\epsilon)$, where c^ϵ is defined for $\epsilon > 0$ by $c^\epsilon_j = c'_j$ for $j < m$ and $c^\epsilon_j = c_{m-1} + \epsilon(j-m+1)$ for $j \geq m$. Moreover, for $\epsilon > 0$ small enough we obtain $s_L(x;c^\epsilon) - s_L(y;c^\epsilon) + s_H(x;c^\epsilon) - s_H(y;c^\epsilon) < 0$. Consequently, $s(x;c^\epsilon) < s(y;c^\epsilon)$, and so (ii) must not hold. A similar argument covers the second case where $s_H(x;c^\epsilon) < s_H(y;c^\epsilon)$, hence in either case (ii) will fail to hold.

Theorem 5 Let x and y be any two distributions having the same median category. Then x FD y if and only if $s_L(x;c) \leq s_L(y;c)$ and $s_H(x;c) \geq s_H(y;c)$ for every scale c.

Proof Let x and y have the same median category m. Suppose that x FD y, so that $Y_k - X_k \geq 0$ for all k. Then by (A5) and (A6) we have both $\mu_L(x;c) \geq \mu_L(y;c)$ and $\mu_H(x;c) \geq \mu_H(y;c)$ for every scale c. Since x and y have the same median category, it follows that $s_L(x;c) \leq s_L(y;c)$ and $s_H(x;c) \geq s_H(y;c)$ for every scale c. Conversely, if x FD y does not hold, then there must be some k=1,...,n-1 for which $Y_k - X_k < 0$. If $k < m$, then one can find a scale c' for which $\mu_L(x;c') < \mu_L(y;c')$ and hence $s_L(x;c) > s_L(y;c)$. Alternatively, if $k \geq m$, then there is a scale c' for which $\mu_H(x;c') < \mu_H(y;c')$ and hence $s_H(x;c') < s_H(y;c')$. Either way, the condition "$s_L(x;c) \leq s_L(y;c)$ and $s_H(x;c) \geq s_H(y;c)$ for every scale c" fails to hold, which completes the proof.

ENDNOTES

1.A second problem is that many key health variables can only be expressed as rates over population subgroups. Using data such as these, one can only measure *between-group* inequality, and the results would be conditional on the nature of the groupings.

2.See for example: Kunst, Geurts, and van den Berg (1995) and van Doorslaer et al (1997), who examine international differences in socioeconomic inequality in SRHS; Deaton and Paxson (1998), who evaluate the distribution of SRHS over the life-cycle; and Kennedy, Kawachi, Glass and Prothrow-Stith (1998), who study socioeconomic differences in SRHS in the United States.

3.See for example Singer et al (1976), Mossey and Shapiro (1982), Idler and Angel (1990), Grant et al (1995), and Appels et al (1996), who examine the validity of SRHS as a predictor of mortality. Idler and Kasl (1995) and Marmot et al (1995) relate SRHS responses to other health indicators and outcomes.

4.See for example Manning, Newhouse, and Ware (1982), Anderson and Burkhauser (1985), Butler, Burkhauser, Mitchell and Pincus (1987), Meredith and Siu (1995), Waidmann, Bound, and Schoenbaum (1995), Strauss and Thomas (1998), and Dwyer and Mitchell (1999).

5.This is an adaptation of the reasoning behind the well-known "Borda count" in social choice theory that was applied by Sen (1976) to poverty measurement.

6.To be precise, Deaton and Paxson (1997, 1998) use a linear "ill-health" scale in which 5 is the lowest category and 1 is the highest. In the present paper, the order is reversed.

7.This point is made forcefully by Le Grand and Rabin (1986), who contend "it is surely preferable first to measure the extent of the inequality in a fashion that does not prejudge the question of causality, and then to examine the possible explanations of it."

8. See Kunst (1999) for a review of the literature.

9.Data are taken from the nationally-representative *NHIS*. Sampling weights added by the survey have been applied. See Section 4 for a more extensive discussion of the *NHIS*.

10.The figure employs the scale c=[1, 4.6, 4.96, 4.996, 5], which is concave in that the gap $(c_{i+1} - c_i)$ is strictly decreasing in i.

11.This partial-sum definition of first order dominance is reminiscent of the definition of Lorenz dominance in the context of income distributions. Note that in the present context the entries in the distributions correspond to numbers of persons rather than numbers of dollars.

12.Note that if there are only two health categories there is always comparability using first order dominance. Consequently, reversals of the type discussed above require there to be at least three categories, which is typically the case with SRHS data.

13. At the very least, it makes basic facts about a distribution difficult to report. For instance, all but two of the observations in $x'=(1,1,25,0,1)$ are above the mean when the linear scale c is used; yet all but one are below it when the scale changes to c'. It is hard to imagine how one would respond to a policy-maker's question "what percentage of the population has above-average health?"

14.In this example $\sigma^2(x;c)=1.43 < \sigma^2(y;c)=1.63$ and $\sigma^2(x;c')=5.12 < \sigma^2(y;c')=4.93$. The variances of x and y at the old scale c about the new means $\mu(x;c')$ and $\mu(y;c')$ are respectively 1.92 and 1.91.

15.On the use of partial orderings in related contexts, see Foster and Sen (1997).

16.An analogous approach for income distributions was introduced by Foster and Wolfson (1993).

17.Thus S is a median-based analogue of the Robin Hood index in income inequality analysis, which indicates how much would have to be taken from the "rich" (above the mean) and given to the "poor" (those below the mean), to obtain a completely equal distribution. See Atkinson and Micklewright (1992) for a description of the Robin Hood index, and Kennedy et al (1996), who use the index to analyze income inequality and health across the United States.

18.Deaton and Paxson's scale increases in ill-health, whereas the scale used here increases in health. Nevertheless, inequality orderings using variance or the S index introduced above are equivalent for an equidistant scale whether it increases in ill-health or health.

19.At higher ages, there is also the question of how sample selection due to death affects trends in the dispersion of health. While it is clear that mean health would be lower if the deceased within a cohort were somehow included in the sample, it is not clear how their inclusion would affect life-cycle patterns in dispersion. The effect of excluding institutionalized individuals from the sample on dispersion is similarly unclear, though such selection likely raises the mean.

20.Using *NHIS* data from 1983-1994, Deaton and Paxson (1997) regress specific percentiles of SRHS (scaled 1,2,3,4,5) on age and cohort and find that cohort effects show little statistical significance.

21.Data are a cross-section from the 1994 *NHIS*. The seven income bands: under $9,999, $10,000 to $14,999, $15,000-$24,999, $25,000-$34,999, $35,000-$49,999, and $50,000 and above. The 10-year age groups were: 0-9 years, 10-19 years, and the 20s, 30s, 40s, 50s, 60s, 70s, and 80s.

22.Another way to express this finding is that health poverty, measured against various SRHS categorical thresholds, does not necessarily increase continuously with age among the poor elderly. Once again, it is unclear how sample selection due to death and institutionalization affects these findings.

23.See for example Kennedy, Kawachi and Prothrow-Stith (1996) and Kaplan et al (1996), who relate income inequality to state health levels, and Kennedy et al (1999), who examine differences in the health status of men and women.

24.Medicaid, for example, facilitates large intra- and inter-state redistributions of resources, targeting aid to many of those with the greatest health needs, including the aged, the poor, the disabled, and those with large medical bills.

25.The *NHIS State Data Files* append state identifiers to standard *NHIS* data. To maintain the confidentiality of respondents, variables from the *NHIS* that are included in the *NHIS State Data Files* are aggregated, e.g., continuous variables are categorized. Several small states are grouped together due to small sample sizes, and two states, Nebraska and North Dakota, are not sampled by the *NHIS*.

26.A direct method of standardization was employed. For any given state k=1...25, the adjusted number of people in each SRHS category i is given by the equation

$SRHS_{ki}^{A} = \Sigma_{d=1}^{D}\left[SRHS_{kdi} / n_k\right] * \left[\pi_{kd} / \pi_d\right] * n_k$, or $SRHS_{ki}^{A} = \Sigma_{d=1}^{D} SRHS_{kdi} * \left[\pi_{kd} / \pi_d\right]$, where $SRHS_{kdi}$ is the unadjusted number of people in state k and age/sex category d in SRHS category i, π_{kd} is the proportion of state k's population in age/sex category d, and π_d is the same proportion for the nation as a whole. Since the *NHIS State Data Files* report age in six categories, D = 6 * 2 = 12.

27.We included only the largest states in our analysis in order to minimize the effects of sampling error due to the potential non-representativeness of the state sub-samples in the *NHIS*.

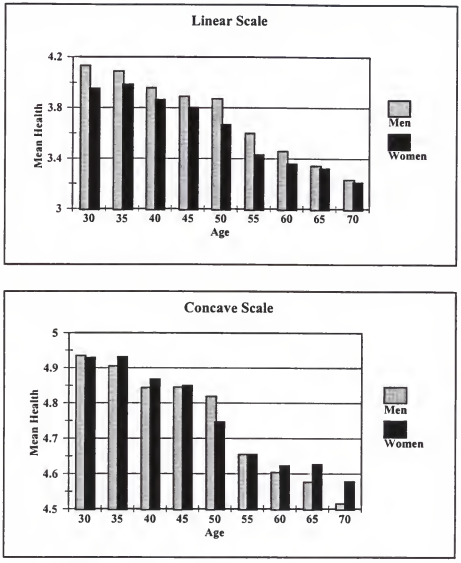
28.In fact, a comparison of health across census regions using data from all states included in the 1994 *NHIS* found a complete first order ordering as follows: the Northeast had the most overall health, followed by the Midwest, the West, and the South.

29.The health poverty rate is defined as the proportion of a population whose health status is no greater than the minimum acceptable health category, or the poverty threshold. This approach to robust poverty comparisons was initiated by Foster and Shorrocks (1988) in the context of income distributions.

30.Wagstaff and Van Doorslaer (1994) and Deaton and Paxson (1997, 1998) discuss the potential importance of concavity in this context.

31. For example, Jencks and Torrey (1988) analyze responses to the following question from the U.S.'s General Social Survey: "Taken all together, how would you say things are these days -- would you say that you are very happy, pretty happy, or not too happy?"

32.This question is raised by Wagstaff and Van Doorslaer (1994) in a somewhat different context. Their solution is not applicable to the problem we are addressing. In particular, their method is based on the assumption that all countries have the same latent distribution of health.



Figures 1a, 1b. Mean health comparison of men and women, selected ages, using two different scalings (data source: 1994 *NHIS*).

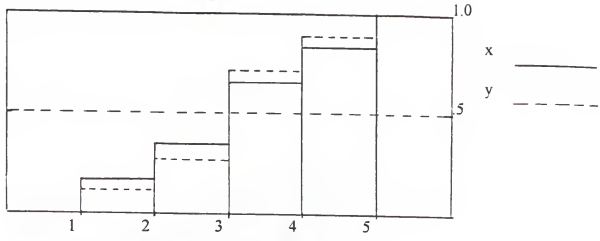


Figure 2. CDFs for x=(4,5,7,5,4) and y=(3,4,11,4,3)

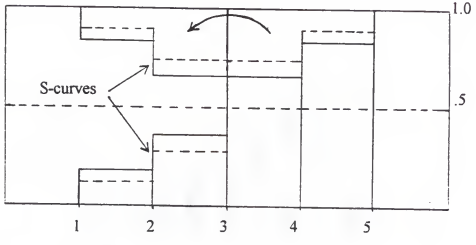


Figure 3. The portions of x and y that lie above the median are 'flipped' across the median to form the upper halves of the S-curves for x and y.

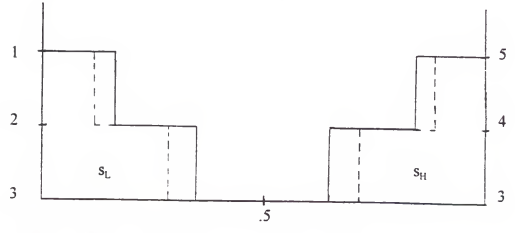


Figure 4. S-curves for x (solid) and y (dashed).

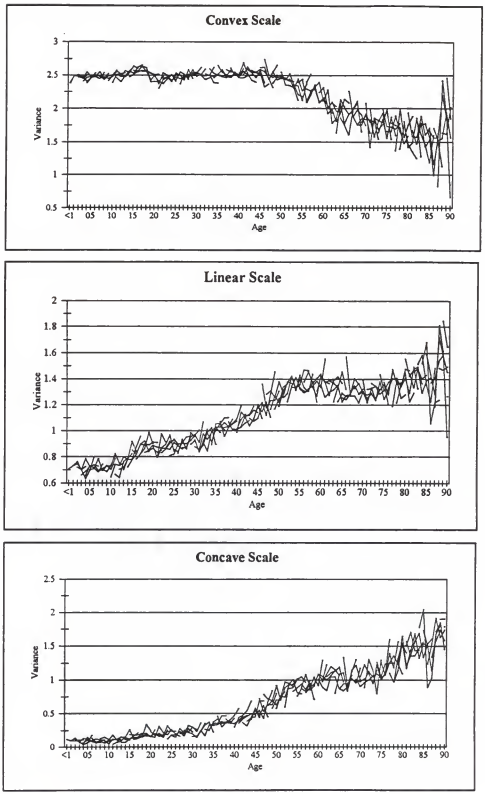


Figure 5. Variance in SRHS for Females. Data grouped by cohort, between 1990 and 1994, using three different scales (data source: 1990-1994 *NHIS*).

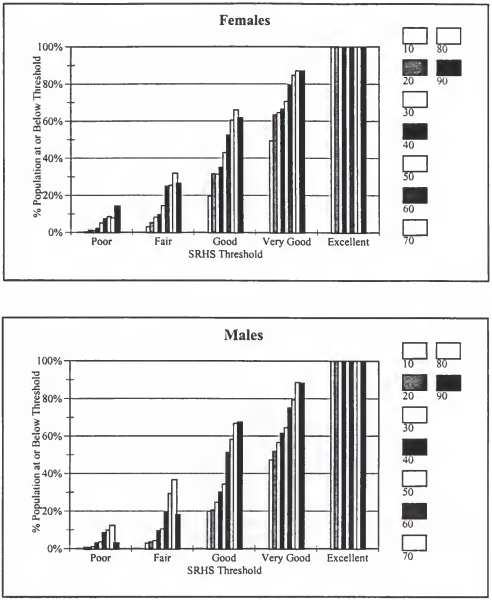


Figure 6. Cumulative probabilities at each SRHS category for selected ages (data source: 1994 *NHIS*).

Age	s	s_L	s_H	Mean	Median	s	s_L	s_H	Mean	Median
10	1.45	1.45	0.00	4.28	Excellent	1.41	1.41	0.00	4.29	Excellent
20	1.49	0.76	0.73	3.99	Very Good	1.46	0.49	0.97	4.24	Very Good
30	1.52	0.80	0.71	3.95	Very Good	1.47	0.60	0.87	4.13	Very Good
40	1.61	0.94	0.67	3.87	Very Good	1.62	0.85	0.77	3.96	Very Good
50	1.84	1.25	0.59	3.67	Very Good	1.68	0.97	0.71	3.87	Very Good
60	2.01	0.65	1.36	3.36	Good	2.03	0.56	1.47	3.46	Good
70	1.78	0.68	1.10	3.21	Good	2.03	0.78	1.24	3.23	Good
80	1.74	0.79	0.94	3.07	Good	1.87	0.98	0.89	2.96	Good
90	1.84	0.81	1.03	3.11	Good	1.30	0.42	0.88	3.23	Good

Table 1. SRHS distributional indicators for females and males using the linear scaling (data source: 1994 NHIS).

	$\hat{s}$	$\hat{s}_L$	$\hat{s}_H$	Mean	Median
Northeast					
Massachusetts	1.65	0.75	0.90	4.08	Very Good
New York	1.58	0.83	0.74	3.96	Very Good
New Jersey	1.66	0.95	0.72	3.89	Very Good
Pennsylvania	1.68	0.91	0.77	3.93	Very Good
Midwest					
Ohio	1.68	0.90	0.78	3.94	Very Good
Indiana	1.66	0.97	0.69	3.86	Very Good
Illinois	1.62	0.86	0.77	3.95	Very Good
Michigan	1.74	1.02	0.72	3.85	Very Good
Wisconsin	1.57	0.84	0.73	3.95	Very Good
Minnesota	1.54	0.69	0.84	4.08	Very Good
Missouri	1.69	0.99	0.70	3.85	Very Good
West					
California	1.74	1.03	0.71	3.84	Very Good
Washington	1.58	0.77	0.81	4.02	Very Good
Colorado	1.71	0.81	0.90	4.04	Very Good
Arizona	1.84	1.10	0.73	3.82	Very Good
South					
Maryland	1.58	0.76	0.82	4.03	Very Good
Virginia	1.66	0.94	0.72	3.89	Very Good
North Carolina	1.87	1.21	0.66	3.73	Very Good
Georgia	1.81	1.02	0.79	3.88	Very Good
Florida	1.77	1.01	0.76	3.87	Very Good
Alabama	1.96	1.35	0.61	3.63	Very Good
Tennessee	1.80	1.12	0.68	3.78	Very Good
Louisiana	1.87	1.10	0.77	3.83	Very Good
Texas	1.80	1.03	0.77	3.87	Very Good
Oklahoma	1.72	0.97	0.75	3.89	Very Good

Table 2. SRHS distributional indicators for the 25 largest states using the linear scale (data source: 1994 *NHIS State Data Files*).

	Northeast				Midwest							West				South										
	MA	NY	NJ	PA	OH	IN	IL	MI	WI	MN	MO	CA	WA	CO	AZ	MD	VA	NC	GA	FL	AL	TN	LA	TX	OK	Totals
Northeast																										
MA		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
NY	1		0	0	0	0	0	0	0	1	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	4
NJ	1	1		0	1	0	0	0	1	1	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	7
PA	1	0	0		1	0	0	0	0	1	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	5
Midwest																										
OH	1	0	0	0		0	0	0	0	1	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	4
IN	1	1	1	1	1		1	0	1	1	0	0	1	1	0	1	0	0	0	0	0	0	0	0	0	11
IL	1	0	0	0	0	0		0	0	1	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	4
MI	1	1	0	1	1	0	1		1	1	0	0	1	1	0	1	0	0	0	0	0	0	0	0	1	11
WI	1	0	0	0	0	0	0	0		1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2
MN	0	0	0	0	0	0	0	0	0		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MO	1	1	1	1	1	0	1	0	1	1		0	1	1	0	1	1	0	0	0	0	0	0	0	0	12
West																										
CA	1	1	1	1	1	0	1	0	1	1	0		1	1	0	1	1	0	0	0	0	0	0	0	0	12
WA	0	0	0	0	0	0	0	0	0	1	0	0		0	0	0	0	0	0	0	0	0	0	0	0	1
CO	0	0	0	0	0	0	0	0	0	0	0	0	0		0	0	0	0	0	0	0	0	0	0	0	0
AZ	1	1	0	1	1	0	1	0	0	1	0	0	1	1		1	0	0	1	1	0	0	0	1	1	13
South																										
MD	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0		0	0	0	0	0	0	0	0	0	1
VA	1	1	0	1	1	0	1	0	1	1	0	0	1	1	0	1		0	0	0	0	0	0	0	0	10
NC	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1		1	1	0	1	1	1	1	23
GA	1	0	0	0	0	0	0	0	0	1	0	0	1	1	0	1	0	0		0	0	0	0	0	0	5
FL	1	0	0	1	1	0	1	0	0	1	0	0	1	1	0	1	0	0	0		0	0	0	0	0	8
AL	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1		1	1	1	1	24
TN	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	0	0	1	0		0	1	1	19
LA	1	0	0	1	1	0	0	0	0	1	0	0	1	1	0	1	0	0	1	0	0	0		1	0	9
TX	1	0	0	0	1	0	0	0	0	1	0	0	1	1	0	1	0	0	0	0	0	0	0		0	6
OK	1	0	0	1	1	0	1	0	0	1	0	0	1	1	0	1	0	0	0	0	0	0	0	0		8
Totals	20	10	6	12	15	3	11	3	9	22	3	3	19	14	2	19	5	1	4	4	0	2	2	5	5	199

Table 3. First order dominance in SRHS among the 25 largest states. A '1' in a cell indicates that the column state has more overall health than the row state, i.e., th the column state first order dominates the row state (data source: 1994 *NHIS State Data Files*).

	Northeast				Midwest							West				South										
	MA	NY	NJ	PA	OH	IN	IL	MI	WI	MN	MO	CA	WA	CO	AZ	MD	VA	NC	GA	FL	AL	TN	LA	TX	OK	Totals
Northeast																										
MA		0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
NY	0		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
NJ	0	0		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
PA	0	1	0		0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3
Midwest																										
OH	0	1	0	0		0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2
IN	0	0	0	0	0		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
IL	0	1	0	0	0	0		0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2
MI	0	0	1	0	0	0	0		0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	3
WI	0	0	0	0	0	0	0	0		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MN	0	0	0	0	0	0	0	0	0		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MO	0	0	0	0	0	0	0	0	0	0		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
West																										
CA	0	0	0	0	0	1	0	0	0	0	1		0	0	0	0	0	0	0	0	0	0	0	0	0	2
WA	0	0	0	0	0	0	0	0	0	0	0	0		0	0	0	0	0	0	0	0	0	0	0	0	0
CO	0	0	0	0	0	0	0	0	0	1	0	0	1		0	1	0	0	0	0	0	0	0	0	0	3
AZ	0	0	1	0	0	1	0	1	1	0	1	1	0	0		0	1	0	0	0	0	0	0	0	0	7
South																										
MD	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		0	0	0	0	0	0	0	0	0	0
VA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		0	0	0	0	0	0	0	0	0
NC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		0	0	0	0	0	0	0	0
GA	0	1	0	1	1	0	1	0	1	0	0	0	0	0	0	0	1	0		0	0	0	0	0	1	7
FL	0	1	1	0	0	1	0	0	1	0	0	0	0	0	0	0	1	0	0		0	0	0	0	0	5
AL	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		0	0	0	0	0
TN	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		0	0	0	0
LA	0	1	1	0	0	1	1	1	1	0	1	0	0	0	0	0	1	0	0	1	0	0		0	1	10
TX	0	1	1	1	0	1	1	0	1	0	1	0	0	0	0	0	1	0	0	0	0	0	0		0	8
OK	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		2
Totals	0	8	5	2	1	5	4	2	9	2	5	1	1	0	0	1	6	0	0	1	0	0	0	0	2	55

Table 4. S dominance in SRHS among the 25 largest states. A '1' in a cell indicates that the column state has more equal health than the row state, i.e., that the the row state S dominates the column state (data source: 1994 *NHIS State Data Files*).

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